POSITION PAPER

# Soft Computing and Fractal Theory for Intelligent Manufacturing

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**Abstract:**

*We describe in this paper the combination of soft computing techniques and fractal theory for achieving intelligent manufacturing. Soft computing techniques can be used to develop hybrid intelligent systems. Fractal theory can be used to analyze the geometrical complexity of natural and artificial objects. The careful combination of soft computing and fractal theory can provide us with a good mix of intelligent techniques and fractal mathematical tools, which can help in achieving automation of manufacturing processes. We consider in this paper several manufacturing and automation problems that are efficiently solved with the proposed approach.*

***Keywords:*** *fuzzy logic, fractal theory, neural networks*

## 1. Introduction

We describe in this paper, new methods for intelligent manufacturing using soft computing techniques and fractal theory. Soft Computing (SC) consists of several computing paradigms, including fuzzy logic, neural networks, and genetic algorithms, which can be used to create powerful hybrid intelligent systems. Fractal theory provides us with the mathematical tools to analyze the geometrical complexity of natural and artificial objects, and can be used for identification and modeling purposes. Combining SC techniques with fractal theory, we can take advantage of the "intelligence" provided by the computer methods and also take advantage of the descriptive power of fractal mathematical tools. We consider in this paper "intelligent manufacturing" as the use of SC techniques to solve manufacturing problems in industrial plants. The basic manufacturing problems that we are considering in this paper are the problems of controlling the process of production, monitoring and diagnosis faults, and performing quality control. These manufacturing problems are not easy to solve because, in general, real world plants are non-linear dynamical systems, and as a consequence there is no simple way to predict their behavior. For this reason, SC techniques, which are non-linear by nature, can be used to solve these manufacturing problems. Hybrid intelligent systems can be used to solve complex problems of modeling, simulation and control of non-linear dynamical systems (Castillo and Melin, 1997) (Castillo and Melin, 1998).

Fuzzy logic is an area of soft computing that enables a computer system to reason with uncertainty (Castillo & Melin, 2001). A fuzzy inference system consists of a set of if-then rules defined over fuzzy sets. Fuzzy sets generalize the concept of a traditional set by allowing the membership degree to be any value between 0 and 1 (Zadeh, 1965). This corresponds, in the real world, to many situations where it is difficult to decide in an unambiguous manner if something belongs or not to a specific class. Fuzzy expert systems, for example, have been applied with some success to problems of control, diagnosis and classification, just because they can manage the complex expert reasoning involved in these areas of application (Kosko, 1997). The main disadvantage of fuzzy systems is that they can't adapt to changing situations. For this reason, it is a good idea to combine fuzzy logic with neural networks or genetic algorithms, because either one of these last two methodologies could give adaptability to the fuzzy system. On the other hand, the knowledge that is used to build these fuzzy rules is uncertain. Such uncertainty leads to rules whose antecedents or consequents are uncertain, which translates into uncertain antecedent or consequent membership functions (Karnik & Mendel 1998). Type-1 fuzzy systems, like the ones mentioned above, whose membership functions are type-1 fuzzy sets, are unable to directly handle such uncertainties. We also consider, type-2 fuzzy systems, in which the antecedent or consequent membership functions are type-2 fuzzy sets. Such sets are fuzzy sets whose membership grades themselves are type-1 fuzzy sets; they are very useful in circumstances where it is difficult to determine an exact membership function for a fuzzy set.

Neural networks are computational models with learning (or adaptive) characteristics that model the human brain (Jang, Sun & Mizutani, 1997). Generally speaking, biological natural neural networks consist of neurons and connections between them, and this is modeled by a graph with nodes and arcs to form the computational neural network. This graph along with a computational algorithm to specify the learning capabilities of the system is what makes the neural network a powerful methodology to simulate intelligent or expert behavior (Werbos, 1991). Neural networks can be classified in supervised and unsupervised. The main difference is that in the case of the supervised neural networks the learning algorithm uses input-output training data to model the dynamic system, on the other hand, in the case of unsupervised neural networks only the input data is given. In the case of an unsupervised network, the input data is used to make representative clusters of all the data. It has been shown, that neural networks are universal approximators, in the sense that they can model any general function to a specified accuracy and for this reason neural networks have been applied to problems of system identification, control, diagnosis, and time series prediction.

Genetic algorithms and simulated annealing are optimization methodologies based on principles of nature (Jang, Sun & Mizutani, 1997). Both methodologies can also be viewed as searching algorithms because they explore a space using heuristics inspired by nature. Genetic algorithms are based on the ideas of evolution and the biological process that occur at the DNA level. Basically, a genetic algorithm uses a population of individuals, which are modified by using genetic operators in such a way as to eventually obtain the fittest individual (Man, Tang & Kwong, 1999). Any optimization problem has to be represented by using chromosomes, which are a codified representation of the real values of the variables in the problem (Michalewicz, 1996). On the other hand, simulated annealing is based on the thermodynamics of the cooling process in metals. The cooling process in metals has to be done in a controlled way to obtain the desired characteristics in the metal. In this case, the search algorithm uses an energy function, which is decreased in each step according to a cooling schedule. Both, genetic algorithms and simulated annealing can be used to optimize a general function. As consequence, one of the main applications of both methodologies is in the optimization of neural networks and fuzzy systems for specific applications.

Fractal theory is the study of the basic concepts of fractals, fractal geometry and fractal dimension. Fractal geometry is a mathematical tool for dealing with complex systems that have no characteristic length scale (Mandelbrot, 1987). A well-known example is the shape of a coastline. When we see two pictures of a coastline on two different scales, we can't tell which scale belongs to which picture: both look the same. This means that the coastline is scale-invariant or, equivalently, has no characteristic length scale. Other examples in nature are rivers, cracks, mountains, and clouds (Mandelbrot, 1997). Scale-invariant systems, are usually characterized by non-integer "fractal" dimensions. In our case, for manufacturing applications the use of the fractal dimension is as measure of complexity of signals, images or time series. For example, in the case of monitoring and diagnosis, we can use the time series of the relevant variables of the process to identify faults or problems. Another application is when we determine the quality of a product base on certain geometrical characteristics that it posses. In any case, the use of the fractal dimension can help in certain applications where the complexity needs to be analyzed to solve the problems (Castillo & Melin, 2001). Of course, when we combine the use of the fractal dimension with SC techniques, we will be constructing a hybrid intelligent system for a specific manufacturing application.

## 2. Problem Formulation

Our particular point of view is that process control, monitoring and diagnosis, and quality control are problems that can not be considered apart because they are intrinsically related in real-world applications. We show in this paper that process control in non-linear plants can be achieved by using fuzzy logic and/or neural networks. Monitoring and diagnosis can also be achieved by applying fuzzy logic and fractal theory. Automated quality control can be achieved by applying neural networks, fuzzy logic and fractal theory. In each application of the SC techniques to solve a real-world manufacturing problem, we show that the intelligent approach proves to be more efficient and accurate that traditional approaches.

Traditionally, the manufacturing problems mentioned above, have been solved by using classical linear methods and models, which lack the accuracy and efficiency needed in real-world applications. Traditional methods include the use of linear statistical models and simple information systems. We instead, consider more general modeling methods, which include fuzzy logic and neural networks. We also use genetic algorithms for the optimization of the fuzzy systems and neural networks. On the other hand, we use the concept of the fractal dimension to measure the complexity of geometrical objects, which is needed for pattern recognition and time series analysis. A proper combination of these methodologies will result in a hybrid intelligent system that will solve efficiently and accurately a specific manufacturing problem.

The diversity of the manufacturing applications considered in this work, gives an idea of the universality of the hybrid approaches presented here. The hybrid approaches for achieving intelligent manufacturing combine the use of SC techniques with fractal theory. The best combination of SC techniques with the fractal dimension for a specific application may change because of the properties of the system under consideration, but one can always find the hybrid architecture needed for achieving the ultimate goal of intelligent manufacturing. Of course, we still need to do a lot of work in finding out general rules for determining in advance the best combination of techniques for a specific application. The best architecture for intelligent manufacturing applications has to be determined in many cases by a lot of experimental work or by using an evolutionary approach for evolving the design of the intelligent system.

## 3. Soft Computing

We describe briefly in the following lines the basic concepts of soft computing:

### 3.1 Type-1 Fuzzy Logic

Since research on fuzzy set theory has been underway for over 30 years now, it is practically impossible to cover all aspects of current developments in this area (Zadeh, 1965). Therefore, the main goal here is to provide a summary of the basic concepts and operations that are relevant to the study of type-1 fuzzy sets. We also consider the definition of linguistic variables and linguistic values and explain how to use them in type-1 fuzzy rules, which are an efficient tool for quantitative modeling of words or sentences in a natural or artificial language. By interpreting fuzzy rules as fuzzy relations, we describe different schemes of fuzzy reasoning, where inference procedures based on the concept of the compositional rule of inference are used to derive conclusions from a set of fuzzy rules and known facts. Fuzzy rules and fuzzy reasoning are the basic components of fuzzy inference systems, which are the most important modeling tool, based on fuzzy set theory (Sugeno, and Kang, 1988).

### 3.2 Type-2 Fuzzy Logic

We also consider a new area in fuzzy logic, which studies type-2 fuzzy sets and type-2 fuzzy logic systems. Basically, a type-2 fuzzy set is a set in which we also have uncertainty about the membership function. Of course, type-2 fuzzy systems consist of fuzzy if-then rules, which contain type-2 fuzzy sets. We can say that type-2 fuzzy logic is a generalization of conventional fuzzy logic (type-1) in the sense that uncertainty is not only limited to the linguistic variables but also is present in the definition of the membership functions.

Fuzzy Logic Systems are comprised of rules. Quite often, the knowledge that is used to build these rules is uncertain. Such uncertainty leads to rules whose antecedents or consequents are uncertain, which translates into uncertain antecedent or consequent membership functions (Karnik & Mendel 1998). Type-1 fuzzy systems, whose membership functions are type-1 fuzzy sets, are unable to directly handle such uncertainties. We consider type-2 fuzzy systems, in which the antecedent or consequent membership functions are type-2 fuzzy sets. Such sets are fuzzy sets whose membership grades themselves are type-1 fuzzy sets; they are very useful in circumstances where it is difficult to determine an exact membership function for a fuzzy set.

The original fuzzy logic, founded by Lotfi Zadeh, has been around for more than 30 years, and yet it is unable to handle uncertainties (Mendel, 2001). That the original fuzzy logic (type-1 fuzzy logic) cannot do this sounds paradoxical because the word "fuzzy" has the connotation of uncertainty. The expanded fuzzy logic (type-2 fuzzy logic) is able to handle uncertainties because it can model and minimize their effects.

We will also consider type-2 fuzzy logic systems and the comparison to type-1 fuzzy systems (Yager, 1980). Finally, we will address briefly the features and problems of fuzzy modeling with type-2 fuzzy logic, which is concerned with the construction of fuzzy inference systems for modeling a given target system (Wagenknecht & Hartmann, 1988). An application of type-2 fuzzy logic in quality control for manufacturing is shown in (Melin and Castillo, 2002), and an application of type-2 fuzzy logic for plant monitoring is shown in (Castillo and Melin, 2003).

### 3.3 Supervised Learning Neural Networks

Application of fuzzy inference systems to automatic control was first reported in Mamdani's paper (Mamdani, 1974), where a "fuzzy logic controller" (FLC) was used to emulate a human operator's control of a steam engine and boiler combination. Since then, "fuzzy logic control" has been recognized as the most significant and fruitful application for fuzzy logic (Kosko, 1992). In the past few years, advances in microprocessors and hardware technologies have created an even more diversified application domain for fuzzy logic controllers, which range from consumer electronics to the automobile industry. However, without adaptive capability, the performance of fuzzy systems relies exclusively on two factors: the availability of human experts, and the knowledge acquisition techniques to convert human expertise into appropriate fuzzy rules. These two factors substantially restrict the application domain of fuzzy systems.

We present the basic concepts, notation, and basic learning algorithms for supervised neural networks. The main models of this type are: back-propagation of feedforward networks, radial basis networks, and adaptive neuro-fuzzy inference systems (ANFIS). The basic concepts of neural networks and the basic back-propagation learning algorithm are very important (Denker, 1986). The momentum and adaptive momentum learning algorithms can be considered as improved versions of the basic back-propagation algorithm. The radial basis neural networks are also a good alternative when considering using supervised networks. Finally, the adaptive neuro-fuzzy inference system (ANFIS) methodology can be considered a good combination of fuzzy logic and neural networks.

### 3.4 Unsupervised Learning Neural Networks

Unsupervised networks are useful for analyzing data without having the desired outputs; in this case, the neural networks evolve to capture density characteristics of a data phase. We consider the use of competitive learning networks, Kohonen self-organizing networks (Kohonen, 1990), learning vector quantization, and Hopfield networks (Hopfield, 1982). When no external teacher or critic's instruction is available, only input vectors can be used for learning. Such an approach is learning without supervision, or what is commonly referred to as unsupervised learning. An unsupervised learning system evolves to extract features or regularities in presented patterns, without being told what outputs or classes associated with the input patterns are desired. In other words, the learning system detects or categorizes persistent features without any feedback from the environment. Thus unsupervised learning is frequently employed for data clustering, feature extraction, and similarity detection (Bezdek, 1981) (Yager and Filev, 1994).

### 3.5 Genetic Algorithms and Simulated Annealing

We consider here genetic algorithms and simulated annealing, which are two basic search methodologies that can be used for modelling and simulation of complex non-linear dynamical systems. Since both techniques can be considered as general purpose optimization methodologies, we can use them to find the mathematical model which minimizes the fitting errors for a specific problem. On the other hand, we can also use any of these techniques for simulation if we exploit their efficient search capabilities to find the appropriate parameter values for a specific mathematical model. Genetic algorithms can be applied to the problem of finding the best neural network or fuzzy system for a particular problem. We can use a genetic algorithm to optimize the weights or the architecture of a neural network for a particular application. Alternatively, we can use a genetic algorithm to optimize the number of rules or the membership functions of a fuzzy system for a specific problem. These are two important application of genetic algorithms, which can be used in to design intelligent intelligent systems for controlling real world dynamical systems.

Genetic algorithms (GAs) are derivative-free optimization methods based on the concepts of natural selection and evolutionary processes (Goldberg, 1989). They were first proposed and investigated by John Holland at the University of Michigan (Holland, 1975). As a general-purpose optimization tool, GAs are moving out of academia and finding significant applications in many areas. Genetic algorithms have been applied to a variety of domains like robotics (Castillo and Melin, 1999), simulation (Castillo and Melin, 2000), and intelligent control (Castillo and Melin, 2001).

### 3.6 Dynamical Systems

The main goal is to provide a summary of the theory of dynamical systems (Devaney, 1989) with particular emphasis on fractal theory, chaos theory, and chaos control (Pyragas, 1992). In the theory of dynamical systems we need to define what is meant by a dynamical system, then we need to define an attractor, and the concept of the fractal dimension of a geometrical object (Semmes, 2000). The Lyapunov exponents can be used as a measure of the chaotic behavior of a dynamical system (Ogorzalek, 1993). On the other hand, the fractal dimension can be used to classify geometrical objects because it measures the complexity of an object. There are also mathematical methods for controlling chaos in dynamic systems. These methods can be used to control a real dynamic system; however, due to efficiency and accuracy requirements we will be forced to use fuzzy logic to model the uncertainty, which is present when numerical simulations are performed (Castillo and Melin, 1994) (Castillo and Melin, 1995). A new theory of fuzzy chaos has also been proposed (Castillo and Melin, 2002).

## 4. Soft Computing and Fractal Theory for Intelligent Manufacturing

We now describe several applications of the hybrid approach combining soft computing techniques and fractal theory for intelligent manufacturing applications.

### 4.1 Plant Monitoring and Diagnostics

A new hybrid fuzzy-fractal approach for plant monitoring and diagnostics is proposed. We use the concept of the fractal dimension to measure the complexity of a time series of observed data from the plant (Castillo and Melin, 2000). We also use fuzzy logic to represent expert knowledge on monitoring the process in the plant. In the hybrid fuzzy-fractal approach a set of fuzzy if-then rules are used to classify different conditions of the plant. The fractal dimension is used as input linguistic variable in the fuzzy system to improve the accuracy in the classification. An implementation of the proposed approach in a real-world application has shown the effectiveness of the approach (Castillo and Melin, 2003).

Diagnostic systems are used to monitor the behavior of a process and identify certain pre-defined patterns that are associated with well-known problems (Du, 1998). These problems, once identified, imply suggestions for specific solutions. Some diagnostic systems are in the form of a rule-based expert system: a set of rules is used to describe certain patterns. Observed data are collected and used to evaluate these rules. If the rules are logically satisfied, the pattern is identified, and the problem associated with that pattern is suggested. In general, the diagnostic systems are used for consultation rather than replacement of human expert (Chiang,, Russell, & Braatz, 2000).

Most current plant monitoring systems only check a few variables against individual upper and lower limits, and start an audible alarm should each variable move out of its predefined range (Du, Elbestawi, & Wu, 1993). Other more complicated systems normally involve more sensors that provide more data but still follow the same pattern of independently checking individual sets of data against some upper and lower limits. The warning alarm from these systems only carries a meaning that there is something wrong with the process in the plant.

### 4.2 Adaptive Control of Non-Linear Plants

Adaptive model-based control of non-linear plants can be achieved by using soft computing techniques. The general concept of adaptive model-based control is very important. The use of fuzzy logic for adaptive control is described in several research works (Margaliot and Langholtz, 2000). A neuro-fuzzy approach can be proposed to learn the parameters of the fuzzy system for control. A specific non-linear plant has been used to test the hybrid approach for adaptive control. A particular stepping motor was used as test bed in the experiments. The results of the neuro-fuzzy approach were good, both in accuracy and efficiency.

Adaptive control is a method of designing a controller with some adjustable parameters and an embedded mechanism for adjusting these parameters (Castillo & Melin, 2001). Adaptive controllers have been used mainly to improve the controller's performance online. Stepping motors can be used in simple open-loop control systems; these are generally adequate for systems that operate at low accelerations with static loads, but closed loop control may be essential for high accelerations, particularly if they involve variable loads (Betin, Pinchon & Capolino, 2000). If a stepping motor in an open-loop control system is overtorqued, all knowledge of rotor position is lost and the system must be reinitialized; servomotors are not subject to this problem.

Here the application of fuzzy logic is proposed to control the speed of a stepping motor drive. The closed-loop control scheme entails in incorporating engineering knowledge into the automatic control system by using the intuition and experience of the designer. This strategy was proposed by Zadeh (1975), to describe complicated systems, which are hard to analyze using traditional mathematics. Indeed, Mamdani (1974) was the first to report on the application of fuzzy logic to control a small laboratory steam engine. The success of this study led many scientists to attempt to control industrial processes such as chemical reactors, automatic trains, or nuclear reactors using fuzzy algorithms. The results of these experiments showed that, fuzzy controllers perform better, or at least as well as, classical controllers. Moreover, this technique offers the advantage of requiring only a simple mathematical model to formulate the algorithm, which can easily be implemented by a digital computer.

### 4.3 Automated Quality Control in Sound Speaker Manufacturing

A hybrid neuro-fuzzy-fractal approach to solve the problem of automated quality control in sound speaker manufacturing is proposed. Traditional quality control has been done by manually checking the quality of sound after production. This manual checking of the speakers is time consuming and occasionally was the cause of error in quality evaluation. For this reason, we developed an intelligent system for automated quality control in sound speaker manufacturing. The intelligent system has a fuzzy rule base containing the knowledge of human experts in quality control. The parameters of the fuzzy system are tuned by applying the ANFIS methodology using, as training data, a real time series of measured sounds as given by good sound speakers. We also use the fractal dimension to measure the complexity of the sound signal. The intelligent system has been tested in a real plant with very good simulation and experimental results.

The quality control of the speakers was done before by manually checking the quality of sound achieved after production (Dickason, 1997). A human expert evaluates the quality of sound of the speakers to decide if production quality was achieved. Of course, this manual checking of the speakers is time consuming and occasionally was the cause of error in quality evaluation (Loctite, 1999). For this reason, it was necessary to consider automating the quality control of the sound speakers. The fractal dimension (Mandelbrot, 1987) is a measure of the geometrical complexity of an object (in this case, the time series). We tested our neuro-fuzzy-fractal approach for automated quality control during production with real sound speakers with excellent results. Of course, to measure the efficiency of our intelligent system we compared the results of the neuro-fuzzy-fractal approach to the ones by real human experts. The results clearly show that the neuro-fuzzy-fractal approach was better than the manual method because it reduced the time required for testing and also the accuracy was improved slightly.

### 4.4 Intelligent Manufacturing of Televisions

We developed an intelligent system for controlling the electrical tuning process during the manufacturing of televisions (Castillo and Melin, 2003). The electrical tuning problem consists in controlling the imaging system of the television to meet production quality requirements. Traditionally, this tuning process has been performed by human operators by manually adjusting the imaging system in the television. In our approach, we use fuzzy logic to automate the tuning process for the televisions. We use a fuzzy system for controlling the voltage, current, and the time during the tuning process, so that the best possible quality of image is achieved. We also use a specific genetic algorithm for optimizing the parameters and number of rules of the fuzzy system. We have implemented this intelligent system for control in the MATLAB programming language with good simulation results. We compared the fuzzy-genetic approach with other methods for control with very good results. The intelligent system was also tested in a real production plant for several months with very good results.

The basic problem that we are considering here is how to artificially reproduce images in the best way possible in devices like televisions or monitors. While producing televisions or monitors in a plant, we normally have a section in charge of adjusting the imaging system of these devices. Traditionally, a human expert operator adjusts the imaging system by experience using a special remote control and the measurements of voltage and current intensity. We are now considering using an intelligent system for controlling the electrical tuning process of televisions during production. The intelligent system has a knowledge base, consisting of fuzzy if then rules, that contains the expert knowledge about tuning the imaging system of televisions. The main reason for using fuzzy logic is that we need to represent and also reason with uncertainty in this application (Castillo & Melin, 2001). We need to use voltage, current intensity, time, and quality as linguistic variables in the fuzzy rules, and define the membership functions for these variables according to real data about the problem and the knowledge of the experts.

### 4.5 Intelligent Manufacturing of Batteries

Hybrid approaches combine soft computing techniques and mathematical models to achieve the goal of controlling the manufacturing process to follow a desired production plan. We have developed several hybrid architectures that combine fuzzy logic, neural networks, and genetic algorithms, to compare the performance of each of these combinations and decide on the best one for our purpose. We consider here the case of controlling non-linear electrochemical processes to test our hybrid approach for control. Electrochemical processes, like the ones used in battery formation, are very complex and for this reason very difficult to control. We have achieved very good results using fuzzy logic for control, neural networks for modeling the process, and genetic algorithms for tuning the hybrid intelligent system.

We can also use an embedded fuzzy control system for a quality control test in the manufacturing of power batteries. This battery test consists in discharging a battery for a certain time at a constant current value, all depending on the battery model. This system is able to improve on others, as it minimizes the problems presented when the test is initiated and when there are false contacts during the test, protecting the battery itself and test equipment. At the moment, a proportional controller is used that even it has demonstrated to be efficient, it has the disadvantages mentioned above.

In a battery, a process of chemical energy conversion into electrical energy is carried out. The chemical energy contained in the electrode and electrolyte is converted into electrical power by means of electrochemical reactions. When connecting the battery to a source of direct current a flow of electrons takes place for the external circuit, and of ions inside the battery, giving an accumulation of load in the battery. The quantity of electric current that is required to load the battery is determined by an unalterable law of nature that was postulated by Michael Faraday, which is known as the Law of Faraday (Bode, Brodd, & Kordesch, 1977). Faraday found that the quantity of electric power required to perform an electrochemical change in a metal is related to the relative weight of the metal. In the specific case of lead this is considered to be 260 amperes hour per kilogram of positive active material for cell. In practice, more energy is required to counteract the losses due to the heat.

With the purpose of finding out, during the process of formation of the battery, the appropriate values of current intensity without surpassing the limits of temperature (Hehner, & Orsino, 1985), we proposed three systems for intelligent control of the process. The first one uses only fuzzy logic for control and statistical models of the process (Sepulveda, Castillo, Montiel, and Lopez, 1998). The second one uses a neuro-fuzzy approach to develop the fuzzy rules controlling the electrochemical process. The third approach uses neural networks to model the process, fuzzy rules for control and genetic algorithms to tune the membership functions.

## 5. Conclusions

A hybrid fuzzy-fractal approach for plant monitoring has been proposed. An implementation in the MATLAB programming language has been built, to describe in more detail the advantages of the new approach. The hybrid fuzzy-fractal approach combines the advantages of fuzzy logic (expert knowledge representation) with the advantages of the fractal dimension concept (ability to measure object complexity), to achieve efficient monitoring and diagnostics. Simulation results are shown to validate the fuzzy-fractal approach. We have compared the performance of the fuzzy-fractal approach against the use of fuzzy logic, the results show that the use of the fractal dimension improves the performance approximately 10%. A problem yet to be considered, is how to automatically learn (or adapt) the membership functions and rules of the fuzzy system using real data for the problem. A genetic approach could be used to evolve the fuzzy system (including the fractal dimension).

Adaptive model-based control of non-linear plants was described. The implementation of an intelligent fuzzy controller for a specific plant was considered. A neuro-fuzzy approach was applied to learn the parameters of the fuzzy system for adaptive control. The feasibility of fuzzy control for stepping motor drives has been tested and illustrated by simulation and experimentation. The best parameters for the fuzzy controller were determined by using the ANFIS methodology and also by using simulations of the stepping motor dynamics. An experimental system was used to validate experimentally the tracking ability and the insensibility to plant parameter changes.

A neuro-fuzzy-fractal approach to the problem of automating the quality control of sound speakers during manufacturing in a real plant was described. We have implemented an intelligent system for quality control in the MATLAB programming language using the ANFIS approach. We also use the fractal dimension as a measure of geometrical complexity of the sound signals. The intelligent system performs rather well considering the complexity of the problem. The intelligent system has been tested in a real manufacturing plant with very good results. We think that our approach for automating quality evaluation can be used for similar problems with only minor changes in the membership functions and rules.

We described an intelligent system for controlling the electrical tuning process during television manufacturing. We used fuzzy logic to automate the tuning process for the televisions. We used the fuzzy system for controlling the voltage, current intensity, and frequency during the tuning process, so that the best possible quality of image is achieved. We also used a breeder genetic algorithm for optimizing the number of rules and parameters of the fuzzy system for control. We implemented the intelligent system for control in MATLAB with excellent simulation results. The intelligent system was also tested in a real production plant with excellent results.

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